Design of Distributed Optimal Adaptive Receding Horizon Control for Supply Chain of Realistic Size under Demand Disturbances

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KEYWORDS

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ABSTRACT

Supply chain networks are interconnection and dynamics of a demand network. Example subsystems, referred to as stages, include raw materials, distributors of the raw materials, manufacturers, distributors of the manufactured products, retailers, and customers. The main objectives of the control strategy for the supply chain network can be summarized as follows: (i) maximize customer satisfaction, and (ii) minimize supply chain operating costs. In this paper, we applied receding horizon control (RHC) method to a set of large scale supply chains of realistic size under demand disturbances adaptively. Also in order to increase the robustness of the system, we added a move suppression term to cost function.

1. Introduction

A supply chain is a network of facilities and distribution entities (suppliers, manufacturers, distributors, retailers) that performs the functions of procurement of raw materials, transformation of raw materials into intermediate and finished products and distribution of finished products to customers [1,2,3]. Between interconnected entities, there are two types of process flows: information flows, e.g., an order requesting goods, and material flows, i.e., the actual shipment of goods (Fig. 1).

Key elements to an efficient supply chain are accurate pinpointing of process flows and timing of supply needs at each entity, both of which enable entities to request items as they are needed, thereby reducing safety stock levels to free space and capital. The

operational planning and direct control of the network can in principle be addressed by a variety of methods, including deterministic analytical models, stochastic analytical models, and simulation models, coupled with the desired optimization objectives and network performance measures [1].

The significance of the basic idea implicit in the receding horizon control (RHC) has been recognized a long-time ago in the operations management literature as a tractable scheme for solving stochastic multi period optimization problems, such as production planning and inventory management, under the term receding horizon[2].

In a recent paper [3], a model predictive control strategy was employed for the optimization of production/ distribution systems, including a simplified scheduling model for the manufacturing function.The suggested control strategy considers only deterministic type of demand, which reduces the need for an inventory control mechanism [4, 5].

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For the purposes of our study and the time scales of interest, a discrete time difference model is developed [6].

The model is applicable to multi echelon supply chain networks of arbitrary structure. To treat process uncertainty within the deterministic supply chain network model, a model predictive control approach is suggested [7, 8].

Typically, RHC is implemented in a centralized fashion [7]. The complete system is modeled, and all the control inputs are computed in one optimization problem.

In large scale applications, such as power systems, water distribution systems, traffic systems, manufacturing systems, and economic systems, such a centralized control scheme may not be suitable or even possible for technical or commercial reasons [8, 9], it is useful to have distributed or distributed control schemes, where local control inputs are computed using local measurements and reduced order models of the local dynamics. The algorithm uses a receding horizon, to allow the incorporation of past and present control actions to future predictions [10, 11]. As well as, further distributed RHC advantages are less computational complication and lower error risk [12, 13].

In this paper, a distributed adaptive RHC method applied to an inventory management system consist of two suppliers, five plant, ten warehouses, eleven distribution centers and twenty retailers.

Also we added a move suppression term to cost function, that increase system robustness toward changes on demands. Through illustrative simulations, it is demonstrated that the model can accommodate supply chain networks of realistic size under input disturbances.

2. Inventory Management System

In this work, a discrete time difference model is developed (a set of inventory management systems dynamic models) [4].

The model is applicable to multi echelon supply chain networks of arbitrary structure, that *DP* denote the set of desired products in the supply Chain and these can be manufactured at plants, *P*, by utilizing various resources (from suppliers), *S*. The manufacturing function considers independent production lines for the distributed products.

The products are subsequently transported to and stored at warehouses, *W*. Products from warehouses are transported upon customer demand, either to distribution centers, *D*, or directly to retailers, *R*. Retailers receive time varying orders from different customers for different products. Satisfaction of customer demand is the primary target in the inventory management mechanism.
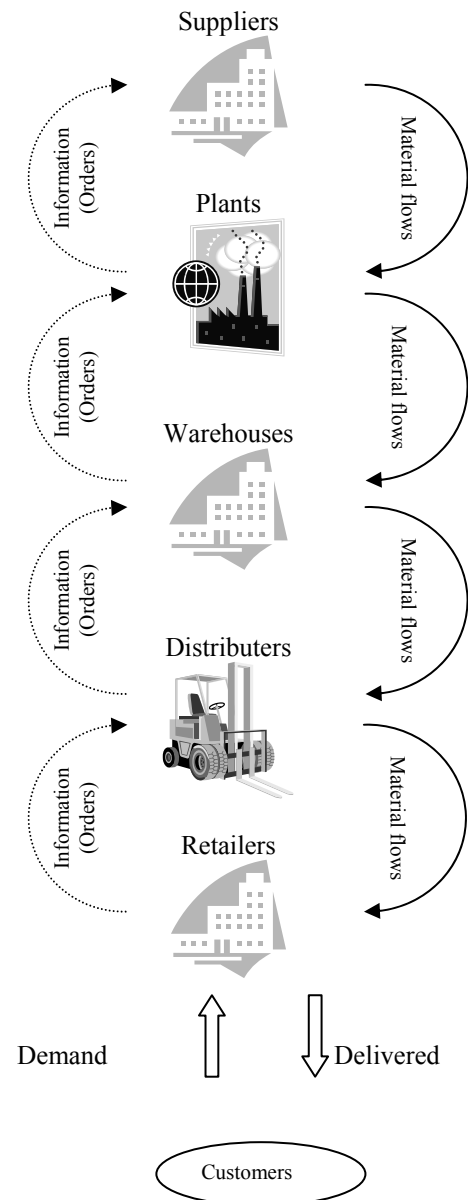

Fig. 1. Supply chain network

Unsatisfied demand is recorded as backorders for the next time period. A discrete time difference model is used to describe the supply chain network dynamics. It is assumed that decisions are taken within equally spaced time periods (e.g. hours, days, or weeks). The duration of the base time period depends on the dynamic characteristics of the network. As a result, dynamics of higher frequency than that of the selected time scale are considered negligible and completely attenuated by the network [4, 14].

Suppliers *S*, Plants *P*, warehouses *W*, distribution centers *D*, and retailers *R* constitute the nodes of the system. For each node, *k*, there is a set of upstream nodes and a set of downstream nodes, indexed by (k', k''). Upstream nodes can supply node *k* and downstream nodes can be supplied by *k*. All valid

(k',k) and/or (k,k'') pairs constitute permissible routes within the network.

All variables in the supply chain network (e.g. inventory, transportation loads) are valid for bulk commodities and products. For unit products, continuous variables can still be utilized, with the addition of a post-processing rounding step to identify neighboring integer solutions. This approach, though clearly not formally optimal, may be necessary to retain computational tractability in systems of industrial relevance.

A product balance around any network node involves the inventory level in the node at time instances t and $t − 1$, as well as the total inflow of products from upstream nodes and total outflow to downstream nodes. The following balance equation is valid for nodes that are either warehouses or distribution centers:

$$y_{i,k}(t) = y_{i,k}(t-1) + \sum_{k'} x_{i,k',k}(t - L_{k',k}) - \sum_{k''} x_{i,k,k''}(t),$$

$$\forall k \in \{P, W, D\}, \qquad t \in T, \qquad i \in DP \tag{1}$$

where $y_{i,k}$ is the inventory of product i stored in node k; $x_{i,k',k}$ denotes the amount of the i-th product transported through route (k',k); $L_{k',k}$ denotes the transportation lag (delay time) for route (k',k), i.e. the required time periods for the transfer of material from the supplying node to the current node. The transportation lag is assumed to be an integer multiple of the base time period.

For retailer nodes, the inventory balance is slightly modified to account for the actual delivery of the i-th product attained, denoted by $d_{i,k}(t)$.

$$y_{i,k}(t) = y_{i,k}(t-1) + \sum_{k'} x_{i,k',k}(t - L_{k',k}) - d_{i,k}(t),$$

$$\forall k \in \{R\}, \qquad t \in T, \qquad i \in DP. \tag{2}$$

The amount of unsatisfied demand is recorded as backorders for each product and time period. Hence, the balance equation for back orders takes the following form:

$$BQ_{i,k}(t) = BQ_{i,k}(t-1) + R_{i,k}(t) - d_{i,k}(t) - LQ_{i,k}(t),$$

$$\forall k \in \{R\}, \qquad t \in T, \qquad i \in DP. \tag{3}$$

where $R_{i,k}$ denotes the demand for the i-th product at the k-th retailer node and time period t. $LO_{i,k}$ denotes the amount of cancelled back orders (lost orders)

because the network failed to satisfy them within a reasonable time limit.

Lost orders are usually expressed as a percentage of unsatisfied demand at time t. Note that the model does not require a separate balance for customer orders at nodes other than the final retailer nodes [4, 15].

3. Receding Horizon Control

The control system aims at operating the supply chain at the optimal point despite the influence of demand changes [12, 13].

The control system is required to possess built in capabilities to recognize the optimal operating policy through meaningful and descriptive cost performance indicators and mechanisms to successfully alleviate the detrimental effects of demand uncertainty and variability.

The main objectives of the control strategy for the supply chain network can be summarized as follows: (i) maximize customer satisfaction, and (ii) minimize supply chain operating costs.

The first target can be attained by the minimization of back-orders (i.e. unsatisfied demand) over a time period because unsatisfied demand would have a strong impact on company reputation and subsequently on future demand and total revenues. The second goal can be achieved by the minimization of the operating costs that include transportation and inventory costs that can be further divided into storage costs and inventory assets in the supply chain network. Based on the fact that past and present control actions affect the future response of the system, a receding time horizon is selected.

Over the specified time horizon the future behavior of the supply chain is predicted using the described difference model (Eq. s (1) − (3)). In this model, the state variables are the product inventory levels at the storage nodes, y, and the back orders, BO, at the order receiving nodes.

The manipulated (control or decision) variables are the product quantities transferred through the network's permissible routes, x, and the delivered amounts to customers, d.

Finally, the product back orders, BO, are also matched to the output variables. The inventory target levels (e.g. inventory setpoints) are time invariant parameters. The control actions that minimize a performance index associated with the outlined control objectives are then calculated over the RHC.

At each time period the first control action in the calculated sequence is implemented. The effect of unmeasured demand disturbances and model mismatch is computed through comparison of the actual current demand value and the prediction from a stochastic disturbance model for the demand variability. The difference that describes the overall demand uncertainty and system variability is fed back into the

receding horizon control scheme at each time period facilitating the corrective action that is required.

The centralized mathematical formulation of the performance index considering simultaneously back orders, transportation and inventory costs takes the following form [4]:

$$
\begin{aligned}
J_{total} =& \sum_{t}^{t+P} \sum_{k \in \{P,W,D,R\}} \sum_{i \in DP} \left\{ w_{y,i,k} (y_{i,k}(t) - y_{s,i,k}(t))^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{k \in \{P,W,D,R\}} \sum_{i \in DP} \left\{ w_{x,i,k',k} (x_{i,k',k}(t) - x_{target})^2 \right\} \\
&+ \sum_{t}^{t+P} \sum_{k \in \{R\}} \sum_{i \in DP} \left\{ w_{BOi,k} (BO_{i,k}(t))^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{k \in \{P,W,D,R\}} \sum_{i \in DP} \left\{ w_{\Delta x,i,k',k} (x_{i,k',k}(t) - x_{i,k',k}(t-1))^2 \right\}
\end{aligned}
\tag{4}
$$

The performance index, *J*, in compliance with the outlined control objectives consists of four quadratic terms.

Two terms account for inventory and transportation costs throughout the supply chain over the specified prediction and control horizons (*P, M*). A term penalizes back orders for all products at all order receiving nodes (e.g. retailers) over the prediction horizon *P*.

Also a term penalizes deviations for the decision variables (i.e. transported product quantities) from the corresponding value in the previous time period over the control horizon *M*. The term is equivalent to a penalty on the rate of change in the manipulated variables and can be viewed as a move suppression term for the control system. Such a policy tends to eliminate abrupt and aggressive control actions and subsequently, safeguard the network from saturation and undesired excessive variability induced by sudden demand changes. In addition, transportation activities are usually preferred to resume a somewhat constant level rather than fluctuate from one time period to another.

However, the move suppression term would definitely affect control performance leading to a more sluggish dynamic response.

The weighting factors, $w_{y,i,k}$, reflect the inventory storage costs and inventory assets per unit product, $w_{x,i,k',k}$, account for the transportation cost per unit product for route (k',k). Weights $w_{BO,i,k}$ correspond to the penalty imposed on unsatisfied demand and are estimated based on the impact service level has on the company reputation and future demand. Weights $w_{\Delta x,i,k',k}$ are associated with the penalty on the rate of change for the transferred amount of the *i*-th product through route (k',k).

Even though, factors $w_{y,i,k}$, $w_{x,i,k',k}$ and $w_{BO,i,k}$ are cost related that can be estimated with a relatively good accuracy, factors $w_{\Delta x,i,k',k}$ are judged and selected mainly on grounds of desirable achieved performance. Also a constant non-negative target logistical input was indicated by x_{target}.

The weighting factors in cost function also reflect the relative importance between the controlled (back orders and inventories) and manipulated (transported products) variables. Note that the performance index of cost function reflects the implicit assumption of a constant profit margin for each product or product family. As a result, production costs and revenues are not included in the index. But in this paper, a distributed formulation will used, namely centralized cost function divided to distributed cost functions for each stage (plant, warehouse, distribution center, retailer):

$$
\begin{aligned}
J_1 =& \sum_{t}^{t+P} \sum_{i \in DP} \left\{ w_{y,i,k} (y_{i,k}(t))^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{i \in DP} \left\{ w_{x,i,k',k} (x_{i,k',k}(t) - x_{target})^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{i \in DP} \left\{ w_{\Delta x,i,k',k} (x_{i,k',k}(t) - x_{i,k',k}(t-1))^2 \right\}, \quad k \in P
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
J_2 =& \sum_{t}^{t+P} \sum_{i \in DP} \left\{ w_{y,i,k} (y_{i,k}(t))^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{i \in DP} \left\{ w_{x,i,k',k} (x_{i,k',k}(t) - x_{target})^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{i \in DP} \left\{ w_{\Delta x,i,k',k} (x_{i,k',k}(t) - x_{i,k',k}(t-1))^2 \right\}, \quad k \in W
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
J_3 =& \sum_{t}^{t+P} \sum_{i \in DP} \left\{ w_{y,i,k} (y_{i,k}(t))^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{i \in DP} \left\{ w_{x,i,k',k} (x_{i,k',k}(t) - x_{target})^2 \right\} \\
&+ \sum_{t}^{t+M} \sum_{i \in DP} \left\{ w_{\Delta x,i,k',k} (x_{i,k',k}(t) - x_{i,k',k}(t-1))^2 \right\}, \quad k \in D
\end{aligned}
\tag{7}
$$

Since supply chains works sequentially, and stages update their policies in series, each node by a distributed local RHC optimizes only for its own policy, and communicates the most recent policy to those nodes to which it is coupled. The RHC corresponding to retailers (with Eq. s (2),(3),(8)) only

will optimize for its own local policy and then will sent its optimal inputs to upstream joint nodes to those nodes which it is coupled (distribution centers), as measurable disturbances.

$$
\begin{aligned}
J_4 = {} & \sum_{t}^{t+P}\sum_{i\in DP}\left\{w_{y,i,k}(y_{i,k}(t))^2\right\} \\
& + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{x,i,k',k}(x_{i,k',k}(t)-x_{t\arg et})^2\right\} \\
& + \sum_{t}^{t+P}\sum_{i\in DP}\left\{w_{BO,i,k}(BO_{i,k}(t))^2\right\} \\
& + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{\Delta x,i,k',k}(x_{i,k',k}(t)-x_{i,k',k}(t-1))^2\right\}, \quad k\in R.
\end{aligned}
\tag{8}
$$

Also the RHC corresponding to distribution centers (with Eq. s (1), (7)) only will optimize for its own local policy and then will sent its optimal inputs to upstream joint nodes to those nodes which it is coupled (warehouse centers), as measurable disturbances, and the RHC corresponding to warehouses (with Eq. s (1), (6),) will optimize for its own local optimal inputs. At last, the RHC corresponding to plants (with Eq. s (1), (5),) will optimize for its own local optimal inputs.

In this paper, distributed RHCs in each stage are updated in each time period and the first control action in the calculated sequence is implemented, and this procedure for next time periods is continued. I
n fact, the distributed RHC corresponding to retailers will done for regulating local inventory level in R and then will sent its receding horizon control optimal inputs at long prediction horizon to upstream joint nodes to those nodes which it is coupled (distribution centers), as measurable disturbances.

Also the RHC corresponding to distribution centers will optimize and then will sent its local optimal inputs to upstream joint nodes to those nodes which it is coupled (warehouse centers), as measurable disturbances. Finally, RHCs corresponding to warehouses and plants will optimize for local optimal inputs.

In fact, as shown in Fig. 2 distributed RHCs of four stages in large scale supply chain management system, dependently and sequentially, operate and produce local constrained predictive control.

4. Simulations

A supply chain system of realistic size is used in the simulated examples [3]. The supply chain network consists of two suppliers, five plant, ten warehouses, eleven distribution centers and twenty retailers (Fig. 3). In the Fig. 3, Due to the multiplicity of connection lines between warehouse nodes and distribution nodes, and between distribution nodes retailer nodes, bus is

used. All possible connections between immediately successive echelons are permitted.

One product family consist of 12 products is being distributed through the network. Inventory setpoints, maximum storage capacities at every node, and transportation cost data for each supplying route for deterministic demand are reported in Table 1.
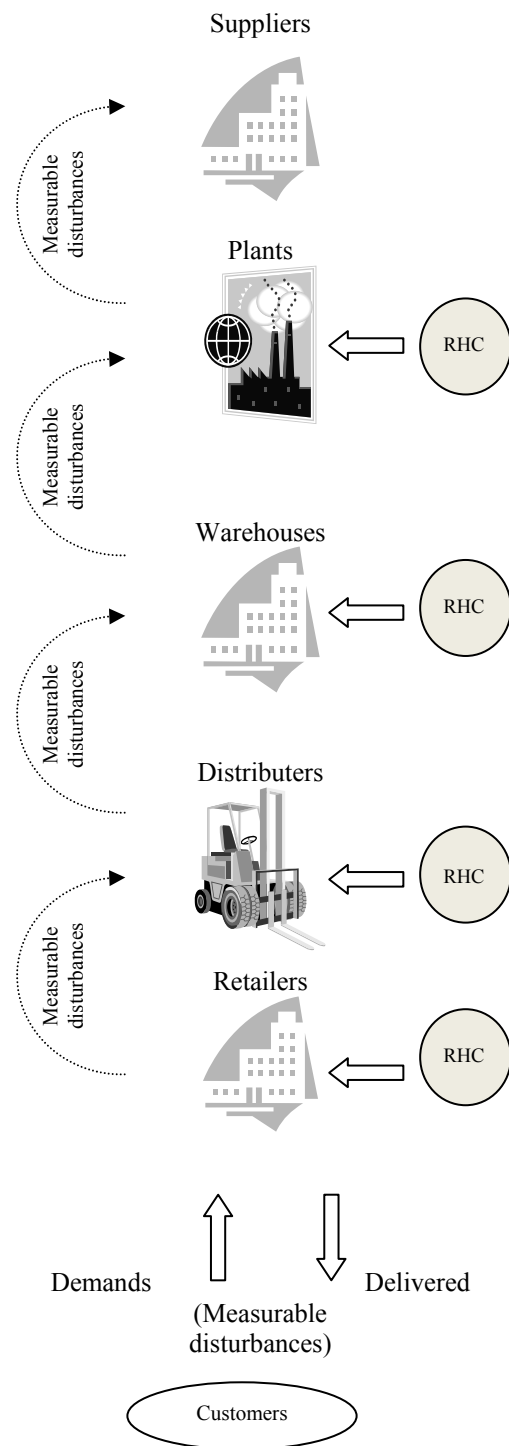

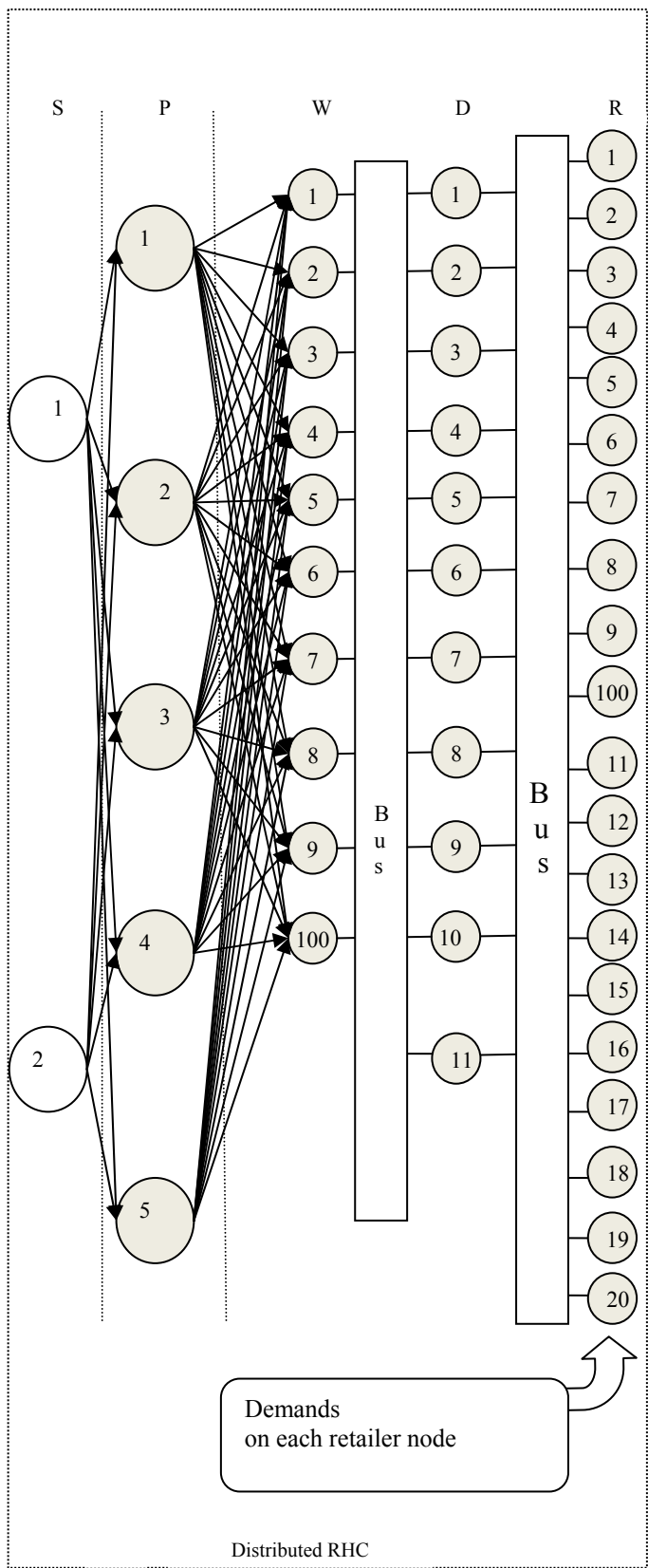**Fig. 2. Distributed RHCs on large scale supply chain**

Fig. 3. Schematic representation of the RHC framework in a multiechelon supply chain

Tab. 1. Supply chain data for deterministic demand

Echelon	P	W	D	R
Max inventory level	800	400	200	100
Inventory setpoint (initial inventory)	300	200	100	30
Transportation cost (move suppression cost)	S to P 1	P to W 0.8	W to D 0.7	D to R 0.7
Inventory weights	1	1	1	1
Back-order weights	-	-	-	0.5
Initial inventory	0	0	0	0
Delays	4	3	2	1

A prediction horizon of 10 time periods and a control horizon of 5 time periods were selected and were considered $LO_{t,k} = 2$ for every time. Each delay was replaced by its 3th order Pade approximation (after system model transform to continuous time model and then return to discrete time model). In this part, centralized and decentralized (distributed) RHC methods were applied to large scale supply chain under constant and pulsatory demands. The simulated scenarios lasted for 300 time periods.

As shown in Fig. s 4 to 7 for constant demand equal 20, and in Fig. s 8 to 11 for pulsatory demand, as demand is deterministic, both centralized and decentralized methods have almost similar responses, and in all these simulations, inventory setpoints are satisfied. (Average inventory levels and average input in each echelon).

In fact, if demand was deterministic, all variables are predicted. But if suddenly demand changed (stochastic demand), RHC method by online demand prediction in its formulation is efficient. The move suppression term would definitely affect control performance leading to a more sluggish dynamic response.
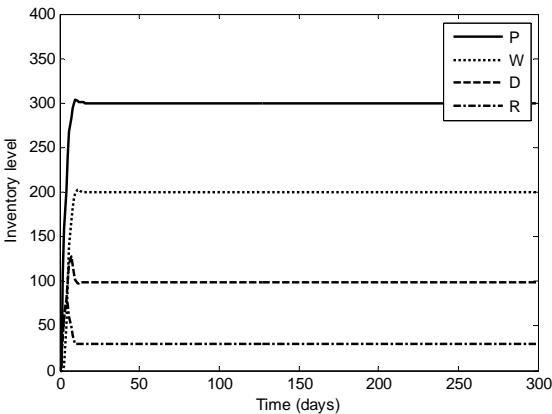

Fig. 4. Discrete time dynamic response to a 20 unit constant demand (centralized RHC)
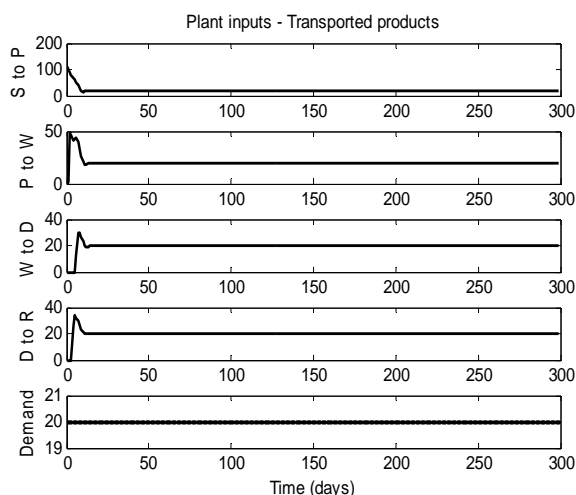
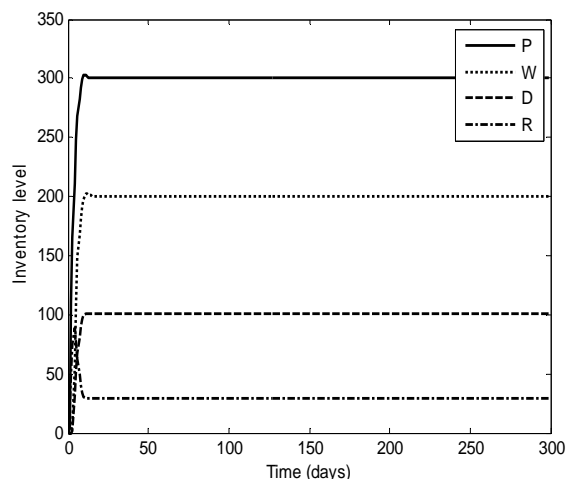**Fig. 5. Plant inputs for a 20 unit constant demand (centralized RHC)**

Fig. 6. Discrete time dynamic response to a 20 unit constant demand (decentralized RHC)
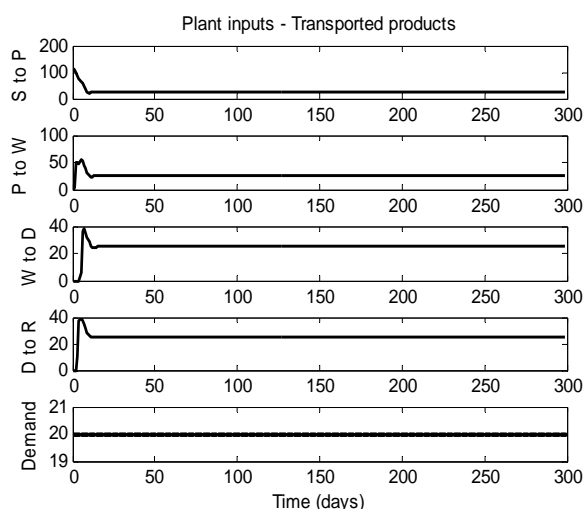

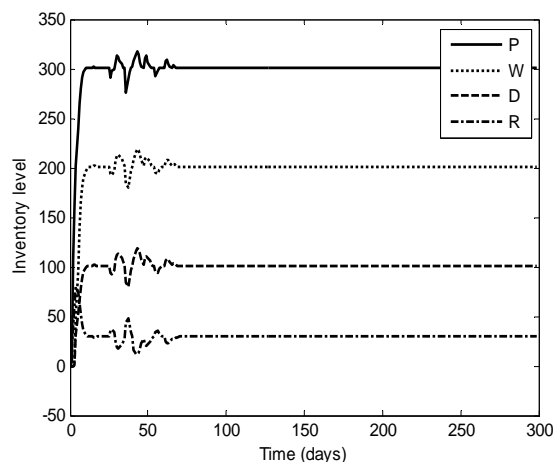**Fig. 7. Plant inputs for a 20 unit constant demand (decentralized RHC)**

Fig. 8. Discrete time dynamic response to pulsatory demand (centralized RHC)
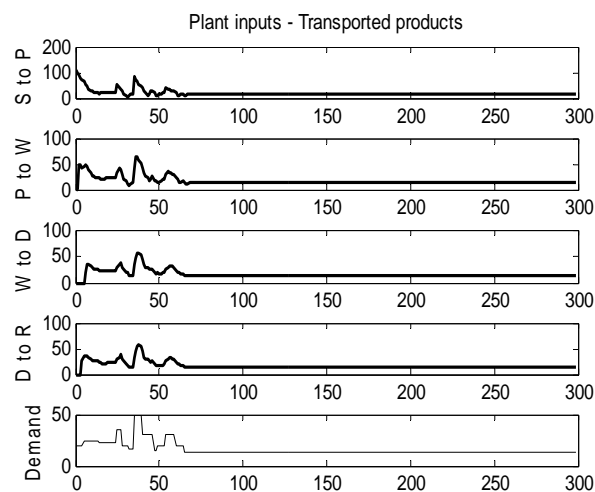

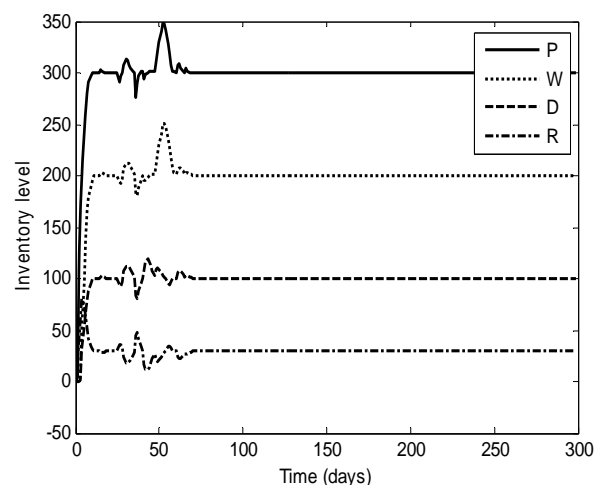**Fig. 9. Plant inputs for pulsatory demand (centralized RHC)**

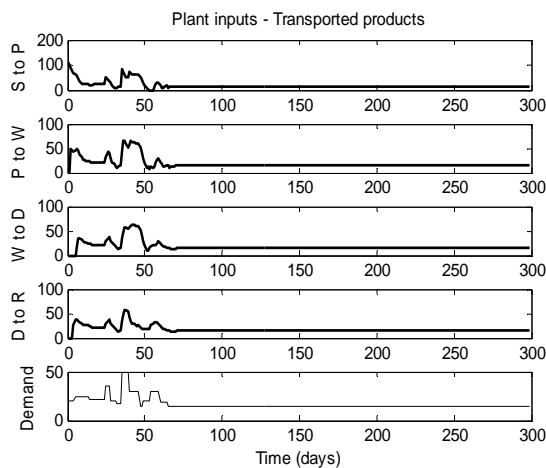**Fig. 10. Discrete time dynamic response to pulsatory demand (decentralized RHC)**

Fig. 11. Plant inputs for pulsatory demand (decentralized RHC)

In this part, centralized and distributed RHC methods are applied to the supply chain network with stochastic variations of customer demand that are defined by an autoregressive integrated moving average (ARIMA (*p, d, q*)) time series model, once with no move suppression term, and once with move suppression term. It is assumed that product demand follows an ARIMA model of the form:

$$R_{i,k}(t) = \frac{\theta(z^{-1})}{\phi(z^{-1})\nabla^d} a_{i,k}(t) \tag{9}$$

$$\forall k \in \{R\}, \qquad t \in T, \qquad i \in DP$$

where $a_{i,k}(t)$ terms denote the independent random shocks with zero-mean Gaussian distributions of a specific variance. z^{-1} is the backward shift operator defined as $z^{-1}a_{i,k}(t) = a_{i,k}(t-1)$ and $z^{-q}a_{i,k}(t) = a_{i,k}(t-q) \cdot \theta(z^{-1})$ and $\varphi(z^{-1})$ are polynomials of order *q* and *p*, respectively. A prediction horizon of 10 time periods and a control horizon of 5 time periods were selected and were considered $LO_{i,k} = 8$ for every time. The accuracy in the prediction of future demand depends on the identification of an accurate ARIMA model. Historical demand data are usually utilized for the identification of the order and parameters of the ARIMA time series model. Correlation among product demands for various retailer nodes can also be introduced through the use of a non-diagonal correlation matrix for the random shocks. In such a case the forecast equations for the product demand become coupled due to cross correlation [4]. The dynamic performance of the network was investigated under the influence of stochastic demand variations. More specifically, an ARIMA (12, 12, 10) time series model was used to forecast the stochastic demand variation.

Inventory setpoints, maximum storage capacities at every node are reported in Table 2. Also transportation

cost data for each supplying route for stochastic demand are reported in Table 3. Inventory levels control faced with discrete stochastic demand with no move suppression effect by centralized RHC method is presented in Fig. s 12 & 13, and by decentralized RHC method is presented in Fig. s 14 & 15. The move suppression effect is demonstrated in Fig. s 16 & 17 for centralized RHC, and in Fig. s 18 & 19 for decentralized RHC.

Tab. 2. Supply chain data for stochastic demand

Echelon	P	W	D	R
Max inventory level	800	400	200	100
Inventory setpoint (initial inventory)	300	200	100	30
Inventory weights	1	1	1	1
Back-order weights	-	-	-	0.5
Initial inventory	0	0	0	0
Delays	4	3	2	1

Tab. 3. Transportation cost for stochastic demand
Transportation cost (move suppression cost)

S to P

$$\begin{bmatrix} 0.2 & 0.5 \\ 0.2 & 0.5 \\ 0.2 & 0.5 \\ 0.2 & 0.5 \\ 0.2 & 0.5 \end{bmatrix}^{T}$$

P to W

$$\begin{bmatrix} 0.5 & 0.2 & 0.5 & 0.5 & 0.5 \\ 0.2 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.2 \\ 0.5 & 0.5 & 0.5 & 0.2 & 0.5 \\ 0.5 & 0.5 & 0.2 & 0.5 & 0.5 \end{bmatrix}^{T}$$

W to D

$$\begin{bmatrix} 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 \end{bmatrix}$$

D to R

$$\begin{bmatrix} 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.2 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \end{bmatrix}$$
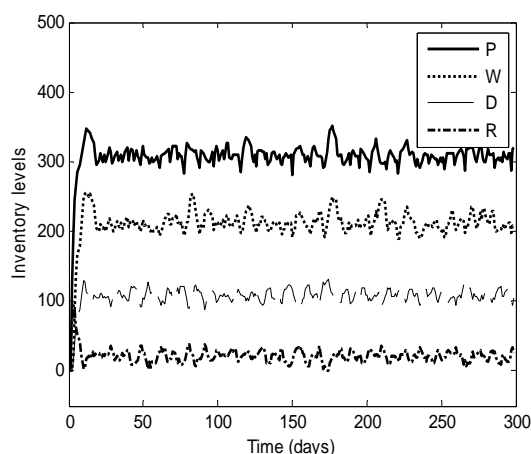
Fig. 12. Inventory levels control by centralized RHC against discrete stochastic demand with no move suppression effect
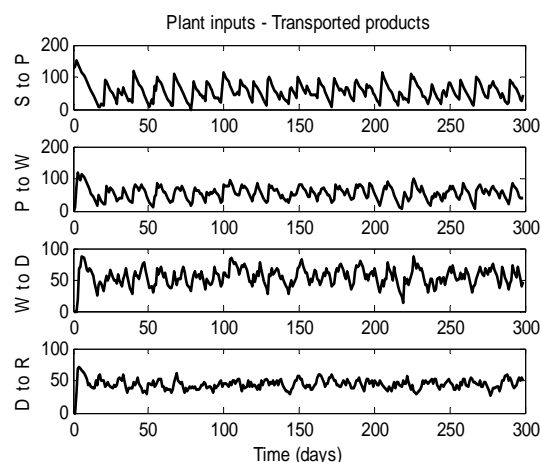

Fig. 13. Plant inputs in centralized RHC against discrete stochastic demand with no move suppression effect
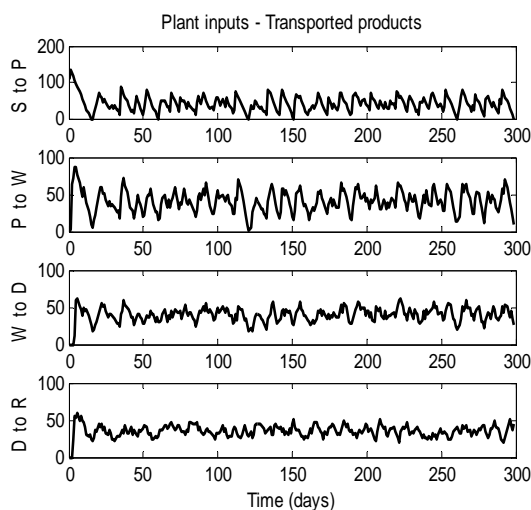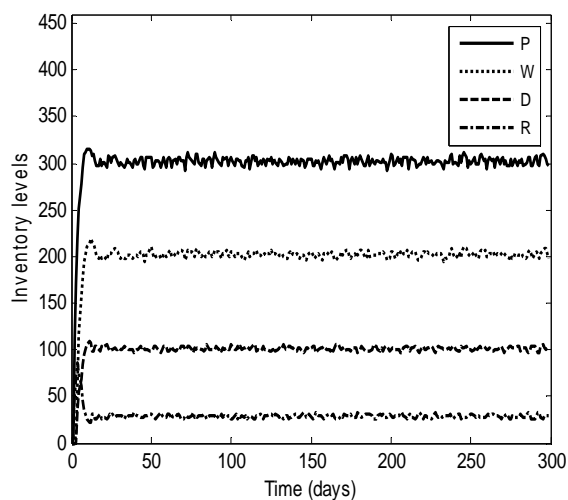

Fig. 14. Inventory levels control by decentralized RHC against discrete stochastic demand with no move suppression effect

Fig. 15. Plant inputs in decentralized RHC against discrete stochastic demand with no move suppression effect

Fig. 16. Inventory levels control by centralized RHC against discrete stochastic demand with move suppression effect
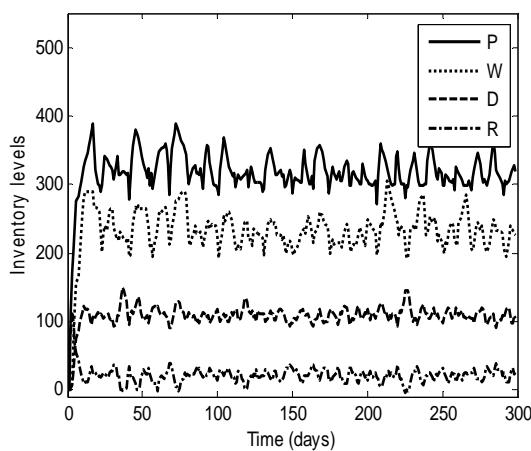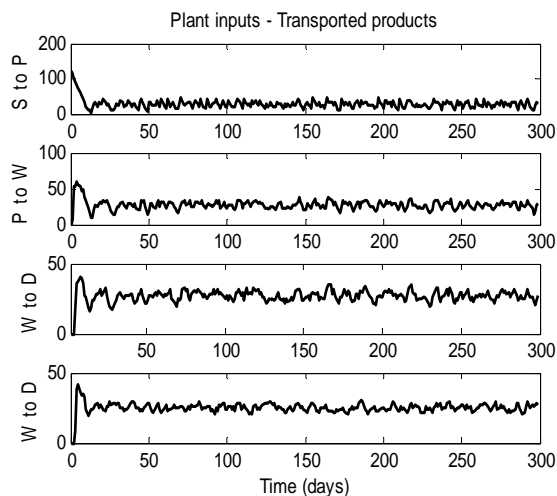

Fig. 17. Plant inputs in centralized RHC against discrete stochastic demand with no move suppression effect

Therefore by using of move suppression, amplitude of variation of demands will be decreased in both centralized and decentralized methods (Fig. s 16 & 18). So move suppression term increased system robustness toward changes on demands. Also, plant inputs are converged to demand average. Efficiency of centralized RHC in response fluctuations decreasing is better than decentralized RHC, but in the case of large scale systems, decentralized method are more practical and more flexible, and have lower risk of error.
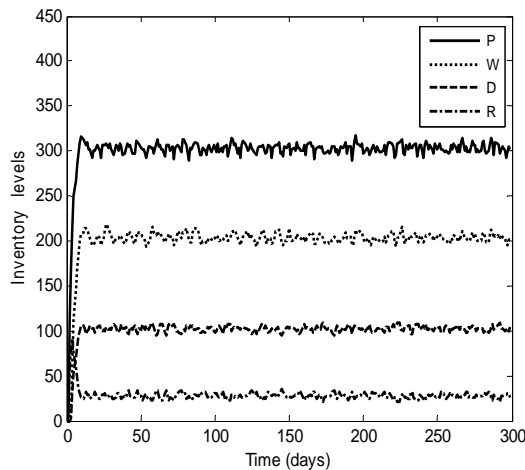

Fig. 18. Inventory levels control by decentralized RHC against discrete stochastic demand with move suppression effect
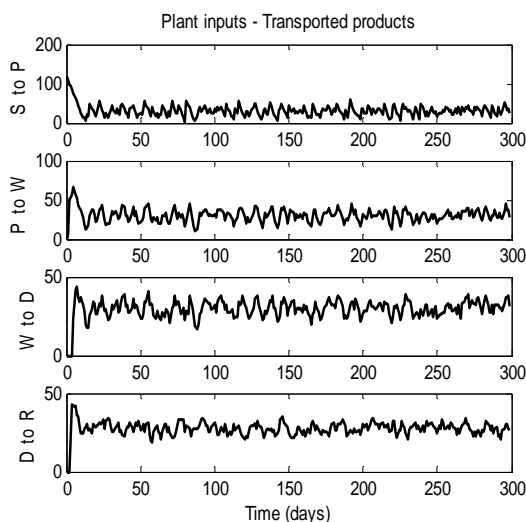

Fig. 19. Plant inputs in decentralized RHC against discrete stochastic demand with no move suppression effect

5. Conclusion

Typically, RHC is implemented in a centralized fashion. In large scale applications, such as manufacturing systems, and economic systems, such a centralized control scheme may not suitable or even possible for technical or commercial reasons, it is useful to have distributed or distributed control schemes, where local control inputs are computed using local measurements and reduced order models of the local dynamics.

As well as, further distributed RHC advantages are less computational complication and lower error risk. Since supply chains works sequentially, and stages update their policies in series, in decentralized structure, each node by a distributed local RHC optimizes only for its own policy, and communicates the most recent policy to those nodes to which it is coupled.

In this paper, centralized and decentralized (distributed) RHCs were implemented on large scale supply chain and were compared in efficiency. Distributed RHCs in each stage are updated in each time period and the first control action in the calculated sequence is implemented, and this procedure for next time periods is continued. Also a move suppression term add to cost function, that increase system robustness toward changes on demands.

Through illustrative simulations, it is demonstrated that the decentralized model can accommodate supply chain networks of realistic size under disturbances. Finally, the move suppression term increases robustness against demand changes.

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